KATHMANDU UNIVERSITY

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING (DoCSE)

DHULIKHEL, KAVRE

A MINI PROJECT REPORT

ON

Arrhythmia Detection Through ECG Signals

For the course: COMP484

Submitted By:

Atit Pokharel (EE-19)

Polarj Sapkota (EE-53)

Sanskar Lohani (EE-14)

Submitted To:

Dr. Bal Krishna Bal

Associate Professor, DoCSE

September 2022

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1. INTRODUCTION

Since the establishment of cardiovascular pathology diagnosis in the twentieth century, electrocardiogram (ECG) analysis has been established as the fundamental component. The electrical activity of the heart is reflected in the ECG signals. As a result, irregular heartbeat or changes in the ECG waveform are indicators of underlying cardiovascular issues including arrhythmias. The typical 12-lead ECG, which detects electric potentials from 10 electrodes implanted at different locations of the body surface—six in the chest and four in the limbs—is the foundation for non-invasive arrhythmia diagnosis. An early diagnosis is crucial for providing a successful treatment for arrhythmias. Monitoring the electrical activity of the heart for an extended period of time (greater than 24 hours) is necessary for the early diagnosis of some types of transitory, short-lived, or uncommon arrhythmias.

Over the years, the open access to ECG databases [1] has encouraged the successful interdisciplinary collaborations that engineers, physicists, and non-linear dynamics researchers are accustomed to. As a result, numerous methods and approaches for computer-aided ECG arrhythmia classification have been developed. The preprocessing of the ECG signal, the identification of heartbeats, the extraction and selection of features, and finally the creation of the classifier are the four key phases that almost all computer-aided ECG classification approaches follow. The preprocessing of the ECG data and the heartbeat detection, both of which have received much research, are outside the purview of this work [2].

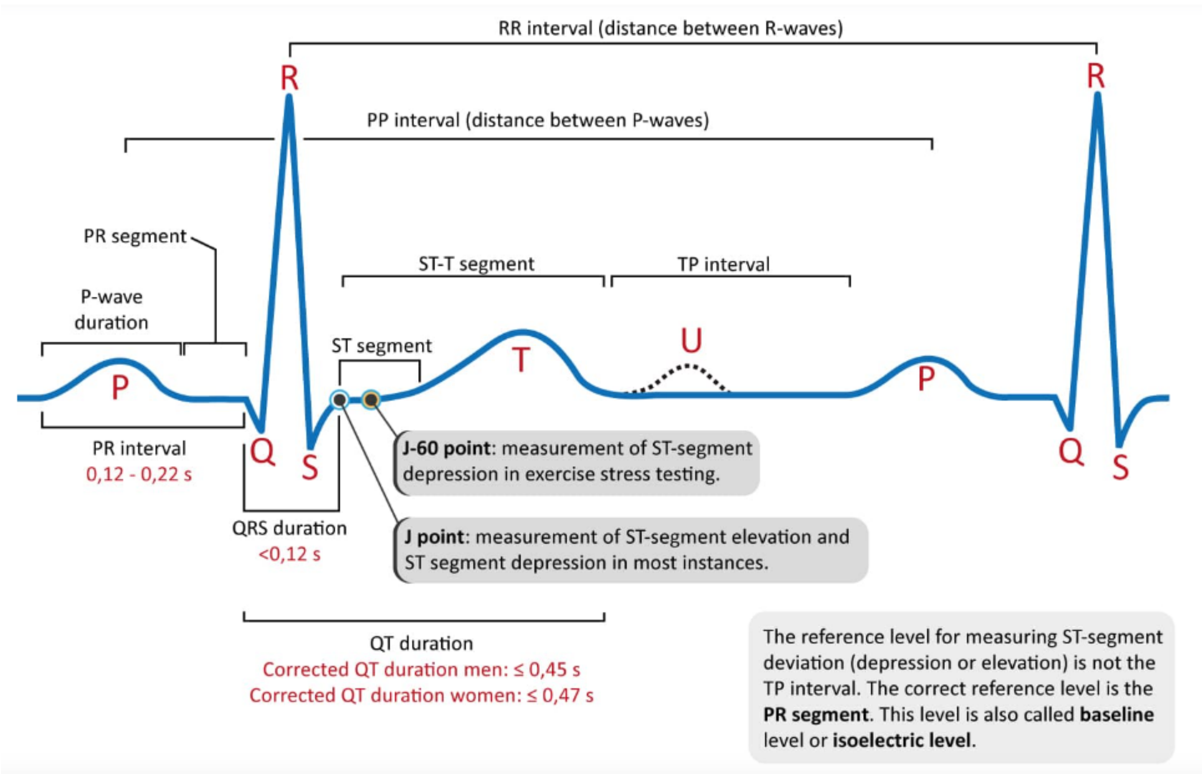
A problem with the rate or rhythm of your heartbeat is known as an arrhythmia. It indicates that your heart is beating either too quickly, too slowly, or irregularly. Tachycardia is the term for an abnormally rapid heartbeat. Bradycardia is the medical term for an excessively sluggish heartbeat. Atrial fibrillation, the most prevalent kind of arrhythmia, results in a rapid and erratic heartbeat.

A large number of classifiers have been proposed for arrhythmia discrimination. We have used an atrificial neural network for the classification of ECG signals i.e. bidirectional LSTM. The proposed model detects especially the most common type of arrhythmia i.e. Atrial Fibrilation.

2. LITERATURE SURVEY

2.1 Basics of ECG

Electrocardiography is the process of producing an electrocardiogram (ECG), a recording of the heart's electrical activity. It is an electrogram of the heart which is a graph of voltage versus time of the electrical activity of the heart using electrodes placed on the skin. These electrodes detect the small electrical changes that are a consequence of cardiac muscle depolarization followed by repolarization during each cardiac cycle (heartbeat).
The ideal ECG Wave is shown in the figure down below.



2.1.1 P Wave

P wave should be always before QRS complex, separated by PQ interval. P wave is a sign of normal atrial depolarization.

Parameters:

duration: 110 ms

amplitude: 0.25 mV

2.1.2 PQ Interval

PQ interval is a period of atrial contraction. The depolarization is delayed in AV node.

Parameters:
duration: 120−200 ms
polarity: isoelectric

2.1.3 QRS Complex

QRS complex represents ventricular depolarization and contraction. There are two phases of ventricular depolarization:

- depolarization of interventricular septum − the vector is oriented from left to right and anteriorly
- depolarization of ventricles − because the left ventricle is more massive than the right ventricle, the vector oriented from right to left and posteriorly.

There are three waveforms in QRS complex:

Q wave − the first negative wave following P wave, may not always be presented
R wave − the first positive wave following P wave or Q wave
S wave − the first negative wave following R wave.

Parameter:
duration of QRS complex: 100 ms or less

2.1.4 ST Segment

ST segment is an isoelectric line, a time period with no electrical activity of the heart. Should be in the same level as PQ interval. Every elevation or depression of this line is pathological. Physiological duration is 320 ms.

2.1.5 T and U Wave

T wave represents repolarization of ventricles. The positivity or negativity should be the same as the major vector of the QRS complex. Physiological duration 160 ms.

The U wave is ordinarily small and follows T wave and usually has the same polarity as T wave.

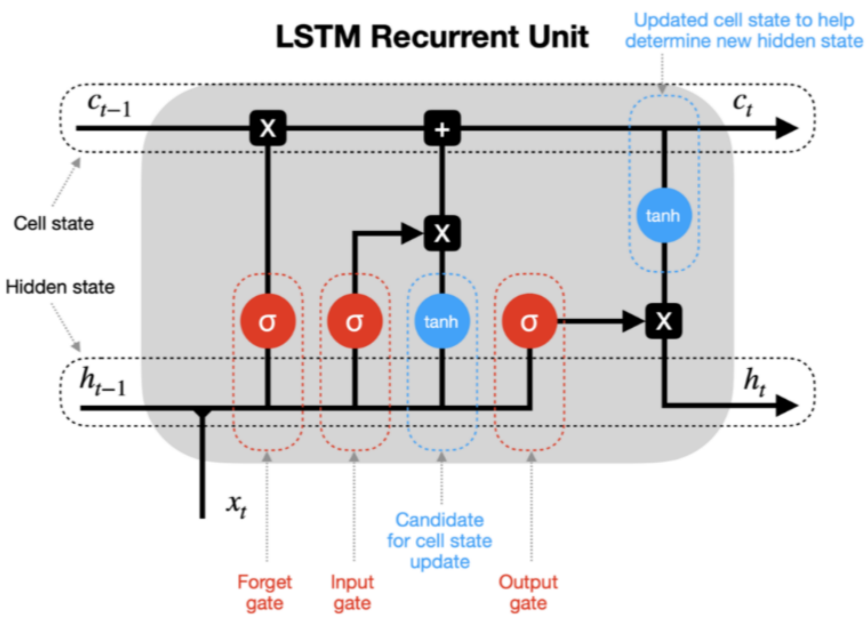
2.1.6 Heart Frequency

Heart frequency or heart rate is based on frequency of ventricular contraction. Can be easy measured from the ECG curve. It is necessary to compare two QRS complexes and measure the time interval between their R waves − RR interval (in seconds):

Rate = 60/RR

Normal heart rate is 55−90/min.

2.2 Neural Networks and LSTM



A few internal contextual state cells in LSTM networks function as long-term or short-term memory cells in a straightforward manner. The status of these cells modulates the LSTM network's output. This is a crucial characteristic when we want the neural network's predictions to take into account the context of earlier inputs as well as the most recent one. Consider the straightforward scenario where we need to foretell the following number in the sequence:

$$6 > 7 > 8 > ?$$

The following output should be 9(x+1), ideally. However, we would like to receive 16 if we provided the following sequence:

$$2 > 4 > 8 > ?\ (2x).$$

Despite the fact that the current last input in both instances was 8, the predicted outcome should differ in each case (when we take into account the contextual information of previous values and not only the last one). By incorporating a loop that lets information to pass from one step to the next, LSTM networks are able to maintain the context of inputs. Recurrent neural networks appear mysterious because of these loops. But if we stop to think about it, each word we read in everything is understood in light of the words that came before it. At each word, we don't just chuck everything away and start over. Similar to this, LSTM predictions are always affected by the inputs' prior experience.

On the other hand, the likelihood that the following output will be dependent on a very old input decreases with time. It is also important to comprehend the context of this temporal dependency distance. Through the use of their forget gate weights, LSTM networks learn when to remember and when to forget. In a straightforward manner, if the forget gate is just a multiplicative factor of 0.9, this factor becomes: $0.9^{10} = 0.348$ (or 65% of information forgotten) after 10 time steps, and after 30 steps, it becomes: 0.04 (96% forgotten).

For our purposes, we can take inspiration from LSTM being used as a music processing tool since they are 2D signals like heart signals. As a series of notes (instead of characters), music can also be generated using LSTM by taking into consideration the notes that have already been played (or combinations of notes). Similarly, irregular heartbeat patterns can be decoded by taking into consideration all the patterns that have already occurred before.

3. METHODOLOGY

3.1 Dataset Preparation and Preprocessing

The ECG dataset was pulled from PhysioNet 2017 Challenge which is available at the archives of Physionet website. The dataset contains 5788 ECG signals directly recorded from real patients including both arrhythmic ones and normal ones.

Firstly, the dataset was loaded in Matlab. As this raw data is not in the Matlab readable form it was then converted into Matlab supported form. After performing this, two separate folders for actual signals and their annotations (pre-classified labels) were obtained.

The recorded signals were of varying length and each signal was sampled with the sampling frequency of 300Hz. Majority of signals were sampled 9000 times and other were varying from very less number rising up to 18000. Signals samples below 9000 times were discarded and those sampled 18000 times were broken down to two signals of 9000 ones. This was done to establish uniformity in the length of the signals.

After this the number of signals was reduced to 5655 which includes 4937 normal ECG signals and 718 abnormal signals.

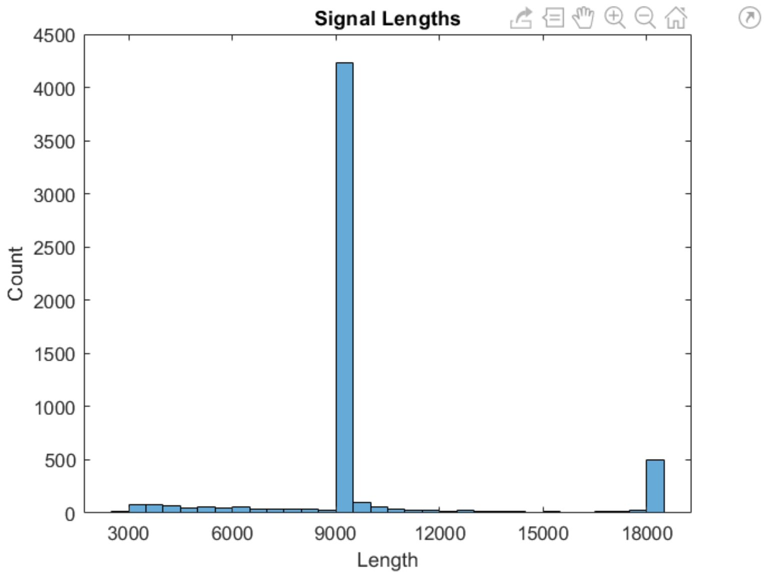


Figure: Histogram showing no. of signals vs their length

Then both abnormal and normal signals were plotted and visualized. While normal heartbeats happen on a regular basis, Abnormal signals heartbeats are spaced out at irregular intervals. Additionally, P waves, which pulse before the QRS complex in a normal heartbeat signal, are frequently absent from Abnormal signals heartbeat signals. The Normal signal's graphic depicts a P wave and a QRS complex.

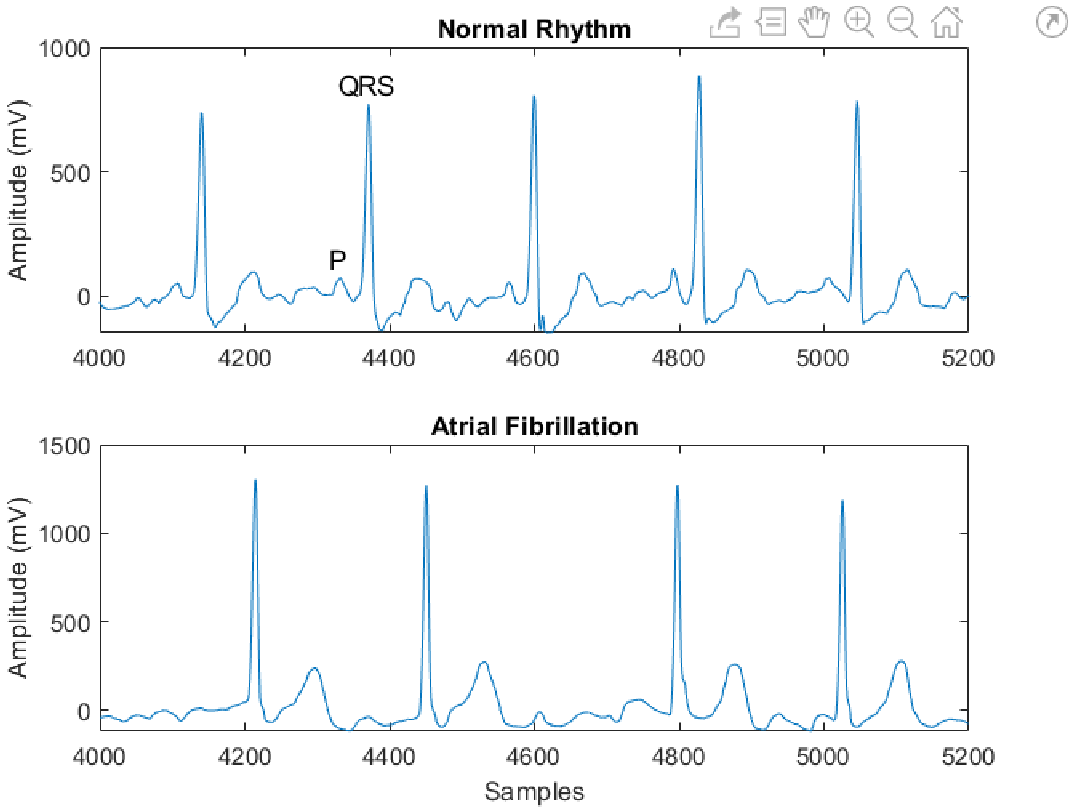


Figure: Normal and Abnormal ECG signal waveforms

3.2 Training the Model

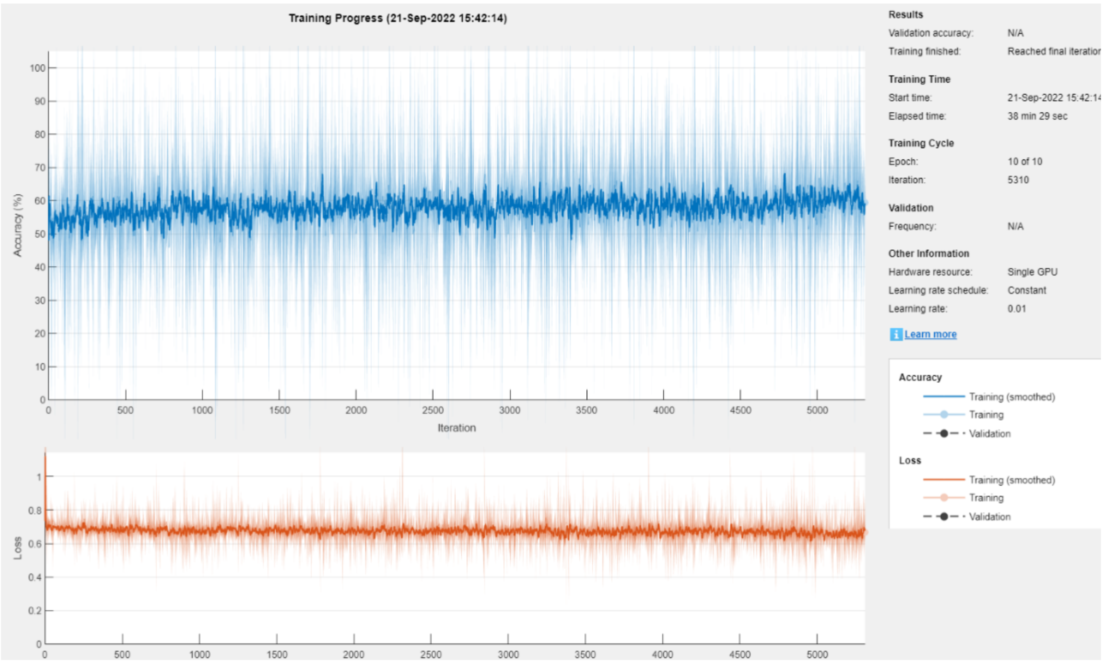
3.2.1 Preparing training and test sets

As there are 4937 Normal signals and 718 Abnormal signals which makes a ratio of 7:1, the classifier would learn that it can achieve a high accuracy by classifying all signals as Normal. This biasing may lead to misclassification of ECG signals. This issue can be simply resolved by oversampling method. This means, the 718 abnormal signals are duplicated to match the same number as Normal signals.
Then a divider function is used to randomly divide data into training and testing sets.

3.2.2 Defining LSTM Network Architecture

Long-term dependencies between sequence data time steps can be learned using LSTM networks. The bidirectional LSTM layer bilstmLayer was employed since it analyzes the sequence both forward and backward. Set the input size to be sequences of size 1 due to the fact that the input signals have only one dimension each. a bidirectional LSTM layer that outputs the last element of the sequence as provided and has an output size of 100. With this command, the input time series is mapped into 100 features by the bidirectional LSTM layer, which then gets ready to generate the output for the fully connected layer. A completely linked layer of size 2 was followed by a softmax layer, a classification layer, and then two classes were provided. Then the training options were specified. The model used adaptive moment estimation (ADAM) solver as it preforms better in LSTM than stochastic gradient descent. Function 'trainNetwork' was used for the process.

3.2.3 Training the Model



The training accuracy, or the classification accuracy for each mini-batch, is shown in the top subplot of the training-progress plot. This value normally rises near 100% as training proceeds effectively. The training loss, which is the cross-entropy loss on each mini-batch, is shown in the bottom subplot. This value normally falls to zero as training progresses satisfactorily.

The accuracy obtained by training the model with this raw data hovered between 55% to 60% which is unacceptable when it comes to medical application. So, the model must be optimized to rise the accuracy.

3.2.4 Feature Extraction and Standardization and Training the Model

Feature extraction from the data can help improve the training and testing accuracies of the classifier. To decide which features to extract, we adapted an approach that computes time-frequency images, such as spectrograms, and uses them to train the model.

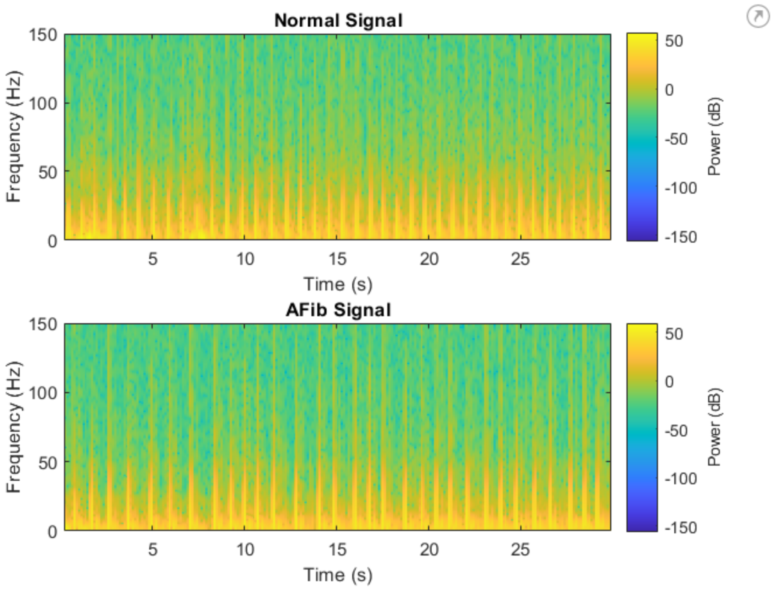


Figure: Spectrogram of both normal and abnormal signals

Features:

- Instantaneous Frequency
- Spectral Entropy

The power spectrogram's initial moment is used by the 'instfreq' function to estimate the time-dependent frequency of a signal. By applying short-time Fourier transformations over time windows, the function generates a spectrogram. The function utilizes 255 time periods in this case. The centers of the time frames are represented by the function's time outputs. Then, the obtained array was visualized.

The spectral entropy gauges how flat and spiky a signal's spectrum is. Low spectral entropy is a property of signals with spiky spectra, such as a sum of sinusoids. White noise, which has a flat spectrum, is an example of a signal with high spectral entropy. Based on a power spectrogram, the 'pentropy' function calculates the spectral entropy.

Then these features from each signal were concatenated with the previous training and test sets. The spectral entropy and instantaneous frequency have means that are almost an order of magnitude different. Furthermore, the LSTM might not be able to learn well since the instantaneous frequency mean is too high. Large inputs may slow down the network's learning and convergence when it is fitted to data with a large mean and wide range of values. The training and testing sets are standardized using the mean and standard deviation from the training set. Then the LSTM architecture was modified accordingly and the data was subjected to train the model.

3. RESULTS

The performance of classification on the training data as well as test data were increased than before. The model shows an accuracy of 94 % in training data and 92% in test data. Both were visualized using the confusion matrix.

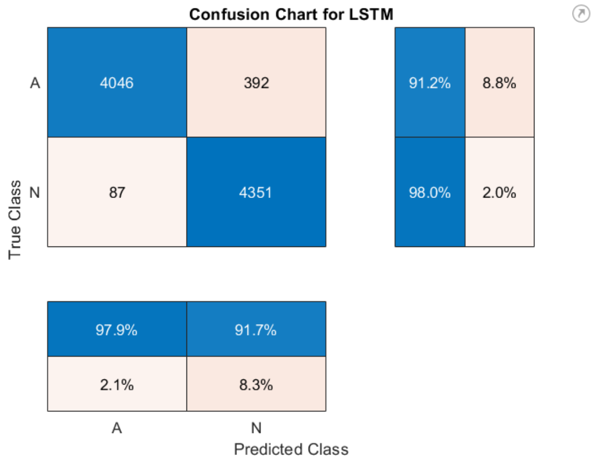


Figure: Performance in Training data

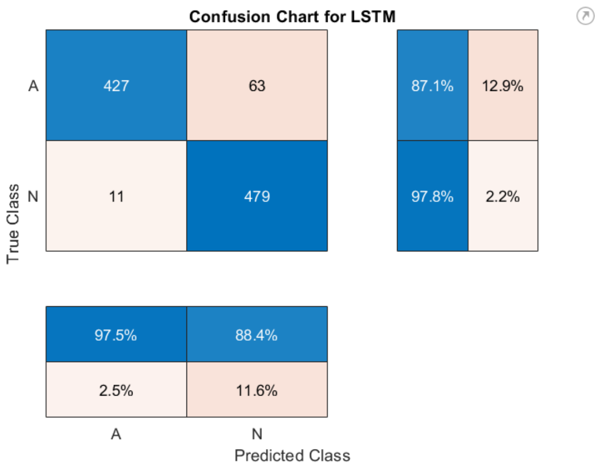


Figure: Performance in test data

4. CONCLUSION

This example shows how to build a classifier to detect atrial fibrillation in ECG signals using an LSTM network. The procedure uses oversampling to avoid the classification bias that occurs when one tries to detect abnormal conditions in populations composed mainly of healthy patients. Training the LSTM network using raw signal data results in a poor classification accuracy. Training the network using two time-frequency-moment features for each signal significantly improves the classification performance and also decreases the training time.

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Link to the github repository